

ENERGY FORECAST DOCUMENTATION
SHORT RANGE AND LONG RANGE
FOR 2023 BUDGET AND BEYOND

Short Range Methodology

This section presents the development of the short-range electric sales forecasts for the Company. Two years of monthly forecasts for electric customers, average usage, and total usage were developed according to Company class and rate structures, with industrial customers further categorized individually or into SIC (Standard Industrial Classification) codes. Residential customers were classified by housing type (single family, multi-family, and mobile homes), rate, and by a statistical estimate of weather sensitivity. For each forecasting group, the number of customers and either total usage or average usage was estimated for each month of the forecast period.

The short-range methodologies used to develop these models were determined primarily by available data, both historical and forecast. Monthly sales data by class and rate are generally available historically. Daily heating and cooling degree data for Columbia and Charleston are also available historically and were projected using a 15-out-of-17-year average of the daily values, after dropping the high and low values for each day. Industrial production indices are also available by SIC on a quarterly basis and can be transformed to a monthly series. Therefore, sales, weather, industrial production indices, and time dependent variables were used in the short-range forecast. In general, the forecast groups fall into two classifications, weather sensitive and non-weather sensitive. For the weather sensitive classes, regression analysis was the methodology used, while for the non-weather sensitive classes regression analysis or time series models based on the autoregressive integrated moving average (ARIMA) approach of Box-Jenkins were used.

The short-range forecast developed from these methodologies was also adjusted for federally mandated lighting programs, net energy metering solar, new industrial loads, terminated contracts, or economic factors as discussed in Section 3.

Regression Models

Regression analysis is a method of developing an equation which relates one variable, such as usage, to one or more other variables which help explain fluctuations and trends in the first. This method is mathematically constructed so that the resulting combination of explanatory variables produces the smallest squared error between the historic actual values and those estimated by the regression. The output of the regression analysis provides an equation for the

variable being explained. Several statistics which indicate the success of the regression analysis fit are shown for each model. Several of these indicators are R^2 , Root Mean Squared Error, Durbin-Watson Statistic, F-Statistic, and the T-Statistics of the Coefficient. PROC REG of SAS was used to estimate all regression models. PROC AUTOREG of SAS was used if significant autocorrelation, as indicated by the Durbin-Watson statistic, was present in the model.

Two variables were used extensively in developing weather sensitive average use models: heating degree days (“HDD”) and cooling degree days (“CDD”). The values for HDD and CDD are the average of the values for Charleston and Columbia. The base for HDD was 60° and for CDD was 75°. In order to account for cycle billing, the degree day values for each day were weighted by the number of billing cycles which included that day for the current month's billing. The daily weighted degree day values were summed to obtain monthly degree day values. Billing sales for a calendar month may reflect consumption that occurred in the previous month based on weather conditions in that period and consumption occurring in the current month. Therefore, this method more accurately reflects the impact of weather variations on the consumption data.

The development of average use models began with plots of the HDD and CDD data versus average use by month. This process led to the grouping of months with similar average use patterns. Summer and winter groups were chosen, with the summer models including the months of May through October, and the winter models including the months of November through April. For each of the groups, an average use model was developed. Total usage models were developed with a similar methodology for the municipal customers. For these customers, HDD and CDD were weighted based on monthly calendar weather. Simple plots of average use over time revealed significant changes in average use for some customer groups. Three types of variables were used to measure the effect of time on average use:

1. Number of months since a base period;
2. Dummy variable indicating before or after a specific point in time; and,
3. Dummy variable for a specific month or months.

Some models revealed a decreasing trend in average use, which is consistent with conservation efforts and improvements in energy efficiency. However, other models showed an increasing average use over time. This could be the result of larger houses, increasing appliance saturations, lower real electricity prices, and/or higher real incomes.

ARIMA Models

Autoregressive integrated moving average (“ARIMA”) procedures were also used in developing the short-range forecasts. For various class/rate groups, they were used to develop customer estimates, average use estimates, or total use estimates.

ARIMA procedures were developed for the analysis of time series data, i.e., sets of observations generated sequentially in time. This Box-Jenkins approach assumes that the behavior of a time series is due to one or more identifiable influences. This method recognizes three effects that a particular observation may have on subsequent values in the series:

1. A decaying effect leads to the inclusion of autoregressive (AR) terms;
2. A long-term or permanent effect leads to integrated (I) terms; and,
3. A temporary or limited effect leads to moving average (MA) terms.

Seasonal effects may also be explained by adding additional terms of each type (AR, I, or MA).

The ARIMA procedure models the behavior of a variable that forms an equally spaced time series with no missing values. The mathematical model is written:

$$Z_t = u + Y_i(B) X_{i,t} + q(B) / f(B) a_t$$

This model expresses the data as a combination of past values of the random shocks and past values of the other series, where:

t	indexes time
B	is the backshift operator, that is $B(X_t) = X_{t-1}$
Z_t	is the original data or a difference of the original data
$f(B)$	is the autoregressive operator, $f(B) = 1 - f_1 B - \dots - f_l B^l$
u	is the constant term
$q(B)$	is the moving average operator, $q(B) = 1 - q_1 B - \dots - q_q B^q$
a_t	is the independent disturbance, also called the random error
$X_{i,t}$	is the ith input time series
$y_i(B)$	is the transfer function weights for the ith input series (modeled as a ratio of polynomials)
$y_i(B)$	is equal to $w_i(B) / d_i(B)$, where $w_i(B)$ and $d_i(B)$ are polynomials in B.

The Box-Jenkins approach is most noted for its three-step iterative process of identification, estimation, and diagnostic checking to determine the order of a time series. The autocorrelation and partial autocorrelation functions are used to identify a tentative model for univariate time series. This tentative model is estimated. After the tentative model has been fitted to the data, various checks are performed to see if the model is appropriate. These checks involve analysis of the residual series created by the estimation process and often lead to refinements in the tentative model. The iterative process is repeated until a satisfactory model is found.

Many computer packages perform this iterative analysis. PROC ARIMA of (SAS/ETS)² was used in developing the ARIMA models contained herein. The attractiveness of ARIMA models comes from data requirements. ARIMA models utilize data about past energy use or customers to forecast future energy use or customers. History on energy use and customers serves as a proxy for all the measures of factors underlying energy use and customers when other variables were not available. Univariate ARIMA models were used to forecast average use or total usage when weather-related variables did not significantly affect energy use or alternative independent explanatory variables were not available.

Electric Sales Assumptions

For short-term forecasting, over 30 forecasting groups were defined using the Company's customer class and rate structures. Industrial (Class 30) Rate 23 was further divided using SIC codes. In addition, thirty-seven large industrial customers were individually projected. The residential class was disaggregated into several sub-groups, starting first with rate. Next, a regression analysis was done to separate customers into two categories, "more weather-sensitive" and "less weather sensitive". The former group is associated with higher average use per customer in winter months relative to the latter group. Finally, these categories were divided by housing type (single family, multi-family, and mobile homes). Each municipal account represents a forecasting group and was also individually forecast. Discussions were held with Industrial Marketing and Economic Development representatives within the Company regarding prospects for industrial expansions or new customers, and adjustments made to customer, rate, or account projections where appropriate. Table 1 contains the definition for each group and Table 2 identifies the methodology used and the values forecasted by forecasting groups.

The forecast for Company Use is based on historic trends and adjusted for Summer 1 nuclear plant outages. Unaccounted energy, which is the difference between generation and sales and represents for the most part system losses, is usually between 4-5% of total territorial sales. The average annual loss for the two previous years was 4.2%, and this value was assumed throughout the forecast. The monthly allocations for unaccounted use were based on a regression model using normal total degree-days for the calendar month and total degree-days weighted by cycle billing. Adding Company Use and unaccounted energy to monthly territorial sales produces electric generation requirements.

TABLE 1 Short-Term Forecasting Groups

<u>Number</u>	<u>Class Name</u>	<u>Designation</u>	<u>Comment</u>
10	Residential Less Weather-Sensitive	Single Family Multi Family	Rates 1, 2, 5, 6, 8, 18, 25, 26, 62, 64 67, 68, 69
910	Residential More Weather-Sensitive	Mobile Homes	
20	Commercial Less Weather-Sensitive	Rate 9 Rate 12 Rate 20, 21 Rate 22 Rate 24 Other Rates	Small General Service Churches Medium General Service Schools Large General Service 3, 10, 11, 14, 16, 18, 25, 26 29, 62, 67, 69
920	Commercial Space Heating More Weather-Sensitive	Rate 9	Small General Service
30	Industrial Non-Space Heating	Rate 9 Rate 20, 21 Rate 23, SIC 22 Rate 23, SIC 24 Rate 23, SIC 26 Rate 23, SIC 28 Rate 23, SIC 30 Rate 23, SIC 32 Rate 23, SIC 33 Rate 23, SIC 99 Rate 27, 60 Other	Small General Service Medium General Service Textile Mill Products Lumber, Wood Products, Furniture and Fixtures (SIC Codes 24 and 25) Paper and Allied Products Chemical and Allied Products Rubber and Miscellaneous Products Stone, Clay, Glass, and Concrete Primary Metal Industries; Fabricated Metal Products; Machinery; Electric and Electronic Machinery, Equipment and Supplies; and Transportation Equipment (SIC Codes 33-37) Other or Unknown SIC Code* Large General Service Rates 18, 25, and 26
60	Street Lighting	Rates 3, 9, 13, 17, 18, 25, 26, 29, and 69	
70	Other Public Authority	Rates 3, 9, 20, 21, 25, 26, 29, 65 and 66	
92	Municipal	Rate 60, 61	Three Individual Accounts

*Includes small industrial customers from all SIC classifications that were not previously forecasted individually. Industrial Rate 23 also includes Rate 24. Commercial Rate 24 also includes Rate 23.

TABLE 2 Summary of Methodologies Used to Produce the Short-Range Forecast

<u>Value Forecasted</u>	<u>Methodology</u>	<u>Forecasting Groups</u>
Average Use	Regression	Class 10, All Groups Class 910, All Groups Class 20, Rates 9, 12, 20, 22, 24, 99 Class 920, Rate 9 Class 70, Rate 3
Total Usage	ARIMA/ Regression	Class 30, Rates 9, 20, 99, and 23, for SIC = 91 and 99 Class 930, Rate 9 Class 60 Class 70, Rates 65, 66
	Regression	Class 92, All Accounts Class 97, One Account
Customers	ARIMA	Class 10, All Groups Class 910, All Groups Class 20, All Rates Class 920, Rate 9 Class 30, All Rates Except 60, 99, and 23 for SIC = 22, 24, 26, 28, 30, 32, 33, and 91 Class 930, Rate 9 Class 60 Class 70, Rate

Long Range Sales Forecast

Electric Sales Forecast

This section presents the development of the long-range electric sales forecast for the Company. The long-range electric sales forecast was developed for six classes of service: residential, commercial, industrial, street lighting, other public authorities, and municipals. These classes were disaggregated into appropriate subgroups where data was available and there were notable differences in the data patterns. The residential, commercial, and industrial classes are considered the major classes of service and account for over 93% of total territorial sales. A customer forecast was also developed for each major class of service.

For the residential class, forecasts were produced for those customers categorized into two groups, more and less weather sensitive. They were further disaggregated into housing types of single family, multi-family and mobile homes. Residential street lighting was also evaluated separately. These subgroups were chosen based on available data and differences in the average usage levels and/or data patterns. Commercial sales were estimated for four subgroups within this sector: small, medium, large, and "other". Small commercial sales were limited to Rate 9 usage; medium was based on Rates 12, 20, 21, and 22; large was Rate 24, and other consisted of the special rates shown in Table 1 in Appendix A. Average use and customer equations were developed for each commercial subgroup, with the resulting sales projections combined to create the total commercial sales forecast. The industrial class was disaggregated into two digit SIC code classification for the large general service customers, while smaller industrial customers were grouped into an "other" category. These subgroups were chosen to account for the differences in the industrial mix in the service territory. Except for the residential group, the forecast for sales was estimated based on total usage in that class of service. The number of residential customers and average usage per customer were estimated separately and total sales were calculated as a product of the two.

The forecast for each class of service was developed utilizing an econometric approach. The structure of the econometric model was based upon the relationship between the variable to be forecasted and the economic environment, weather, conservation, and/or price.

Forecast Methodology

Development of the models for long-term forecasting was econometric in approach and used the technique of regression analysis. Regression analysis is a method of developing an equation which relates one variable, such as sales or customers, to one or more other variables that are statistically correlated with the first, such as weather, personal income or population growth. Generally, the goal is to find the combination of explanatory variables producing the smallest error between the historic actual values and those estimated by the regression. The output of the regression analysis provides an equation for the variable being explained. In the equation, the variable being explained equals the sum of the explanatory variables each multiplied by an estimated coefficient. Various statistics, which indicate the success of the regression analysis fit, were used to evaluate each model. The indicators were R^2 , mean squared Error of the Regression, Durbin-Watson Statistic and the T-Statistics of the Coefficient. PROC REG and PROC AUTOREG of SAS were used to estimate all regression models. PROC REG was used for preliminary model specification, elimination of insignificant variables, and for the final model specifications. Model development also included residual analysis for incorporating dummy variables and an analysis of how well the models fit the historical data, plus checks for any statistical problems such as autocorrelation or multicollinearity. PROC AUTOREG was used if autocorrelation was present as indicated by the Durbin-Watson statistic.

Prior to developing the long-range models, certain design decisions were made:

- The multiplicative or double log model form was chosen. This form allows forecasting based on growth rates, since elasticities with respect to each explanatory variable are given directly by their respective regression coefficients. Elasticity explains the responsiveness of changes in one variable (e.g. sales) to changes in any other variable (e.g. price). Thus, the elasticity coefficient can be applied to the forecasted growth rate of the explanatory variable to obtain a forecasted growth rate for a dependent variable. These projected growth rates were then applied to the last year of the short-range forecast to obtain the forecast level for customers or sales for the long-range forecast. This is a constant elasticity model, therefore, it is important to evaluate the reasonableness of the model coefficients.

- One way to incorporate conservation effects on electricity is through real prices or time trend variables. Models selected for the major classes would include these variables, if they were statistically significant.
- The remaining variables to be included in the models for the major classes would come from four categories:
 1. Demographic variables - Population.
 2. Measures of economic well-being or activity: real personal income, real per capita income, employment variables, and industrial production indices.
 3. Weather variables - average summer/winter temperature or heating and cooling degree-days.
 4. Variables identified through residual analysis or knowledge of political changes, major economics events, etc. (e.g., the gas price spike in 2005 attributable to Hurricane Katrina and recession versus non-recession years).

Standard statistical procedures were used to obtain preliminary specifications for the models. Model parameters were then estimated using historical data and competitive models were evaluated on the basis of:

- Residual analysis and traditional "goodness of fit" measures to determine how well these models fit the historical data and whether there were any statistical problems such as autocorrelation or multicollinearity.
- An examination of the model results for the most recently completed full year.
- An analysis of the reasonableness of the long-term trend generated by the models. The major criteria here was the presence of any obvious problems, such as the forecasts exceeding all rational expectations based on historical trends and current industry expectations.
- An analysis of the reasonableness of the elasticity coefficient for each explanatory variable. Over the years a host of studies have been conducted on various elasticities relating to electricity sales. Therefore, one check was to see if the estimated coefficients from Company models were in-line with other studies. As a result of the evaluative procedure, final models were obtained for each class.

- The drivers for the long-range electric forecast included the following variables.

Service Area Housing Starts
Service Area Real Per Capita Income
Service Area Real Personal Income
State Industrial Production Indices
Real Price of Electricity
Average Summer Temperature
Average Winter Temperature
Heating Degree Days
Cooling Degree Days

The service area data included Richland, Lexington, Berkeley, Dorchester, Charleston, Aiken and Beaufort counties, which account for most total territorial electric sales. Service area historic data and projections were used for all classes except for the industrial class. Industrial productions indices were only available on a statewide basis, so forecasting relationships were developed using that data. Since industry patterns are generally based on regional and national economic patterns, this linking of Company industrial sales to a larger geographic index was appropriate.

Economic Assumptions

In order to generate the electric sales forecast, forecasts must be available for the independent variables. The forecasts for the economic and demographic variables were obtained from IHS Markit, S&P Global. and the forecasts for the price and weather variables were based on historical data. The trend projection developed by IHS Markit, S&P Global is characterized by slow, steady growth, representing the mean of all possible paths that the economy could follow if subject to no major disruptions, such as substantial oil price shocks, untoward swings in policy, or excessively rapid increases in demand.

Average summer temperature (average of June, July, and August temperature) or CDD, and average winter temperature (average of December (previous year), January and February temperature) or HDD were assumed to be equal to the normal values used in the short-range forecast.

After the trend econometric forecasts were completed, reductions were made to account for

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higher air-conditioning and water-heater efficiencies, DSM programs, net energy metering solar, and the replacement of incandescent light bulbs with more efficient CFL or LED light bulbs.

Industrial sales were increased if new customers are anticipated or if there are expansions among existing customers not contained in the short-term projections. Also, electric vehicle (EV) forecasts from Guidehouse were incorporated into the long-range forecasts.

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TABLE 3 Long-Term Forecasting Groups

<u>Number</u>	<u>Class Name</u>	<u>Designation</u>	<u>Comment</u>
10	Residential Less Weather-Sensitive	Single Family Multi Family	Classes 10,13,14
910	Residential More Weather-Sensitive	Mobile Homes	Classes 910,913,914
20	Commercial Small, Medium, Large, Other	Rate 9 Rate 12 Rate 20, 21 Rate 22 Rate 24 Other Rates	Small General Service Churches Medium General Service Schools Large General Service Misc rates combined to 999
30	Industrial Non-Space Heating	SIC 22,24,26,28 SIC 30,32,33 SIC 99 Rate 27, 60 Other	Textile Mill Products Lumber, Wood Products, Furniture and Fixtures (SIC Codes 24 and 25) Paper and Allied Products Chemical and Allied Products Rubber and Miscellaneous Products Stone, Clay, Glass, and Concrete Primary Metal Industries; Fabricated Metal Products; Machinery; Electric and Electronic Machinery, Equipment and Supplies; and Transportation Equipment (SIC Codes 33-37) Other or Unknown SIC Code* Large General Service Westvaco
60	Street Lighting		
70	Other Public Authority		
92	Municipal		Two accounts

TABLE 4 Summary of Methodologies Used to Produce the Long-Range Forecast

<u>Value Forecasted</u>	<u>Methodology</u>	<u>Forecasting Groups</u>
Average Use	Regression, double log	Class 10, All Groups Class 910, All Groups Class 20, small, medium, large, other
Total Usage	Regression, double log	Class 30, SIC 22,24,26,28,30,32,33,99 Westvaco Class 60 Class 70
	Regression, double log	Class 92
Customers	Regression, double log	Class 10 Class 20, small, medium, large, other

Peak Demand Forecast

A demand forecast is made for the summer peak, the winter peak and then for each of the remaining ten months of the year. The summer peak demand forecast, and the winter peak demand forecast is made for each of the six major classes of customers. Customer load research data is summarized for each of these major customer classes to derive load characteristics that are combined with the energy forecast to produce the projection of future peak demands on the system. Interruptible loads and standby generator capacity are captured and used in the peak forecast to develop a firm level of demand. By utility convention the winter season follows the summer season. The territorial peak demands in the other ten months are projected based on historical ratios by season. The months of May through October are grouped as the summer season and projected based on the average historical ratio to the summer peak demand. The other months of the year are similarly projected with reference to the winter peak demand.